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Non-Intrusive Identification of Load Patterns in Smart Homes Using Percentage Total Harmonic Distortion

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Abstract: Demand Response (DR) plays a vital role in a smart grid, helping consumers plan their usage patterns and optimize electricity consumption and also reduce harmonic pollution in a distribution grid without compromising on their needs. The first step of DR is the disaggregation of loads and identifying them individually. The literature suggests that this is accomplished through electric features. Present-day households are using modern power electronic-based nonlinear loads such as LED (Light Emitting Diode) lamps, electronic regulators and digital controllers to reduce the electricity consumption. Furthermore, usage of SMPS (Switched-Mode Power Supply) for computing and mobile phone chargers is increasing in every home. These nonlinear loads, while reducing electricity consumption, also introduce harmonic pollution into the distribution grid. This article presents a deterministic approach to the non-intrusive identification of load patterns using percentage Total Harmonic Distortion (THD) for DR management from a Power Quality perspective. The percentage THD of various combinations of loads is estimated by enhanced dual-spectrum line interpolated FFT (Fast Fourier Transform) with a four-term minimal side-lobe window using a LabVIEW-based hardware setup in real time. The results demonstrate that percentage THD identifies a different combination of loads effectively and advocates alternate load combinations for recommending to the consumer to reduce harmonic pollution in the distribution grid.

Keywords: demand response; load disaggregation; percentage total harmonic distortion and non-intrusive identification of load pattern

1. Introduction

Demand Response (DR) provides an opportunity for consumers to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage from peak time to off peak and/or altering their usage pattern in response to time-based tariffs or other forms of financial incentives to improve Power Quality (PQ). DR also plays an important role in a smart grid in helping consumers plan their consumption pattern and optimize electricity usage without compromising on their needs [1–3], and is made possible through (i) identification of unnecessary consumption of electricity at an individual appliance level, (ii) alerting consumers with timely information that helps to balance the load between appliances and (iii) leading to reduced bills. DR is approached through the following four steps:

- Identification of load features;
- Load disaggregation;
- Developing insights into consumption behavior;
- Actionable recommendations.

1.1. Identification of Load Features

In the past 30 years, researchers have tried several diverse electrical and non-electrical features to uniquely identify all types of home appliances with different operation modes [4]. Event-based techniques have been employed to identify turn-on and turn-off events.

The identification of electrical appliances is possible through their electrical behavior (active power (P) reactive power (Q), voltage (V), current (I), harmonics, power factor (pf), phase angle, etc.). Moreover, PQ and VI trajectories were used as described in [5–7]. These parameters can be at a steady state or transient (turned on). There is some research using non-electrical behaviors such as light emitted (lumens), heat generated (joules), vibration and sound (noise), EMF (Electromagntic Field) produced, etc. If we employ non-electrical behavior to recognize appliances, then we need respective sensors to collect data for analysis. While this method can be considered as non-intrusive from an electricity point of view, it is an expensive proposition and may be invasive from a personal privacy point of view.

A detailed literature review was presented by Antonio Ruano et al. in [4]. As per the review article, the observations of various load features for disaggregation are 1. active power and reactive power, 2. voltage, current and fundamental phase angle, 3. average displacement power factor, 4. VI trajectory and current vectors, 5. steady-state current transients, 6. PQ disturbance trajectories, 7. third and fifth harmonic amplitudes, 8. average Total Harmonic Distortion (THD), 9. the maximum magnitude of the first eight harmonics 10. The rate of change of transient signals, 11. Shannon and Reini entropies, 12. the spectral band energy of the current spectrum, 13. wavelet transform coefficients, 14. features of power spectrum density, 15. occupancy data, 16. usage patterns and 17. Electro-Magnetic Interference (EMI) signals.

It is quite evident that, initially, researchers tried the active power of the load and its steady-state active power (P) features that are readily available in an energy meter for load disaggregation, which requires a low sampling rate at the time of data acquisition. Later, it was found that, due to the additive nature of active power, it is only useful and deterministic when the power ratings of appliances are distinct, and the sum of the power ratings of various combinations of appliances in operation is also distinct. Therefore, the active power feature is suitable mostly for high-power appliances and is not helpful to discern the simultaneous operation of appliances with the same ratings. Later, researchers employed transient power features [8] (ON slope at the start and step changes) to detect appliance status at a higher sampling frequency (high to very high). Load features such as steady-state power characteristics versus transient power characteristics, capturing events like turn-on step changes, are quite cumbersome. Some researchers used multiple harmonics [9] and the harmonic phase [10,11], since they are induced by nonlinear loads, which are small in amplitude.

1.2. Load Disaggregation

Once the features are decided as discussed above, they are used to discern the start time and duration of operation of the appliances. There have been several attempts by various researchers to disaggregate loads using multiple electrical and non-electrical features [4]. Usually, a power supplier provides a single energy meter outside the premises and records the cumulative energy consumption since its installation. Periodic billing (bill cycles) is calculated by subtracting the current reading from the reading taken at the previous bill cycle and applying a tariff. This procedure does not allow the consumer (i) to realize opportunities for saving energy at an appliance level and (ii) to prevent unnecessary consumption before it happens. The most effective method for load disaggregation is to meter the power at every appliance, termed appliance-level monitoring (ALM) [12]. G.W. Hart [13] recognized that ALM is highly prohibitive due to (a) the high number of appliances in use, (b) the various types of appliances and (c) inconsistent times and durations of operation of appliances at home. He proposed, for the first time, in 1992 that there is a need for identifying individual loads without sub-metering [13,14] and termed this Non-Intrusive Appliance Load Monitoring (NIALM), which is now referred to as Non-Intrusive Load Monitoring (NILM).

There are various ways to discern appliances using digital signal processing (DSP), wavelet transform (WT) and artificial intelligence (AI). Recently, machine learning (ML) [15] and deep learning (DL) techniques have been trialed for this purpose. In particular, two types of ML, namely supervised learning (e.g., classification) and unsupervised learning (e.g., clustering), have been widely used for NILM [16–24]. Load features and the selected disaggregation technique decide the sampling rate for data acquisition for the desired accuracy.

A concise and updated review of the various features reported in the literature for NILM and a comprehensive feature selection from a benchmarked dataset are reported in [25]. A multi-objective evolutionary algorithm is proposed in [26], where five objective functions using active power, apparent power, reactive power, current waveform, and harmonics as load signatures are established to identify several electrical appliances. Antonio Ruano et al. [4] carried out an exhaustive review of disaggregation approaches, including the most recent ones, namely machine learning and deep learning, and they are 1. the Hidden Markov Model (HMM), 2. Deep Neural Networks (D-NN), 3. k-NN (K-nearest neighbors) classifiers, 4. Naïve Bayes Classifiers, 5. Tensor and Matrix Factorization, 6. NN auto encoders, 7. Graphic Signal Processing, 8. Multi-Layer Perceptron, 9. linear searches of databases, 10. Maximum a Posteriori probability, 11. fuzzy "C" means, 12. Discriminative Disaggregation Sparse Coding, 13. The Factorial Hidden Markov Model, 14. hierarchical HMM, 15. variants of HMM, 16. Viterbi Decoding, 17. density-based spatial clustering of applications with noise, 18. quadratic discriminant analysis, 19. Modified Combinatorial Optimization, 20. Long- and Short-Term Memory Recurrent Neural Networks, 21. Karhunen–Loève Spectral Decomposition, 22. iterative subsequence dynamic time warping, 23. particle filtering, 24. Maximum a Posteriori (MAP) criteria, 25. Gaussian Process Classifiers, 26. rule-based classifiers, 27. decision trees, 28. Adaboost classifiers, 29. several supervised classifiers, 30. Self-Optimizing Mapping (SOM), 31. Particle Swarm Optimization, 32. Ant Colony Optimization, 33. Siamese Artificial NN, 34. PCA (Principal component analysis), 35. location-aware energy disaggregation frameworks, and microscopic power features and pattern recognition (reported for NILM in [27]).

It is noted that all of these methods are non-deterministic and hence non-repeatable, which are useful for predictions with some certainty, but not to the extent that the inferences and insights of these methods are beneficial for their deployment in production for consumers to respond in real time and realize the benefits then and there. Furthermore, these methods draw correlations, not causations, to effectively convince consumers to change their behavior.

A comparison between traditional non-deterministic NILM methods versus proposed deterministic methods is illustrated in Table 1, and gives reasons for the limitations of machine learning and deep learning techniques over the proposed deterministic experimental approach.

Table 1. Comparison between traditional non-deterministic Non-Intrusive Load Monitoring (NILM) methods versus proposed deterministic method.

Factor	**Non-Experimental, Statistical Approach**	**Experimental Approach**
Establishes	Correlations	Causation
Deals with	Aggregates, general understanding	Individuals, hence specific
Application	Understanding of macroscopic phenomena	Real-time measurement and micro-level control
Bias	Not easy to eliminate bias	Unbiased
Data	Approximations	Real data
Results	Probability, hence not conclusive	Exact, so conclusive
Regularity and repeatability	Mostly	Always

The realization of benefits and the value of DR lie in the accurate measurement of a load feature that could be used by employing a suitable load feature that can determine, with certainty, the consumer demand and suggest alternate propositions for a better response, either from an energy conservation or PQ perspective.

1.3. Developing Insights on Consumption Behavior for Reducing Harmonic Pollution

Most often, the purpose of NILM is stated as potential savings in energy consumption [28]. All the techniques listed in the previous section are data intensive and require high computing power for application in real-time DR and are uneconomical for this purpose. Moreover, these methods are developed for energy conservation only. DR requires a simplification of the approach and should be fast enough to recommend possible opportunities for savings.

1.4. Actionable Recommendations

After disaggregation, the appliance usage pattern of consumers should be analyzed to ascertain opportunities for energy savings or PQ improvement and should recommend the same. The consumer may decide to act upon these recommendations. The consumer benefit lies in the reduction in the unnecessary usage of high-power appliances such as geysers, air conditioning and HVAC (heating, ventilation, and air conditioning). However, the power ratings of these appliances are becoming greener and smarter day by day. At the same time, energy savings on account of the usage of low-power appliances (SMPS, mobile chargers, CFL (compact fluorescent lamp), LED) are not remunerative enough to the consumer. By reviewing the previous literature [29], Kelly, J. et al. assessed that the reduction in domestic electricity consumption on average is 0.7–4.5% only. Usually, consumers are conscious about the usage of high-power appliances, whereas low-power appliances are not considered from an energy savings point of view. Zhuang, M. [30] highlights that there are other good reasons why we need NILM of appliances that employ electronic controls for load demand forecasting accuracy, to provide better criteria for utilities to decide on generation. For the grid operators, NILM additionally allows flexible resource management for DR and tackles the uncertainty derived from renewable sources, apart from energy savings.

1.5. Summary and Proposal

Interestingly, all of the research is focused on energy savings from the high-power appliances of a household, which are usually not a big concern for utilities. The simplification of the DR approach with reasonable accuracy and reliability is the main characteristic that drives its adoption. A schematic of the DR management system is shown in Figure 1, and the generic process is self-explanatory.

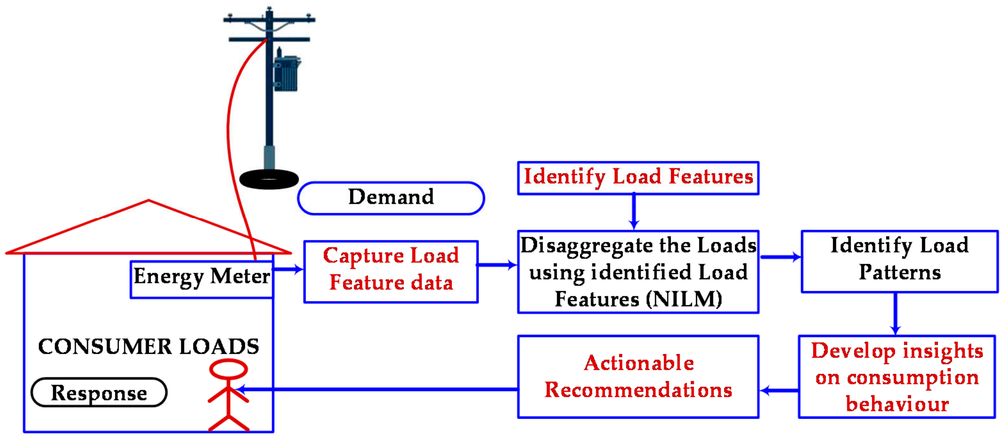

Figure 1. Schematic of Demand Response (DR) management.

The literature suggests that harmonics, harmonic phasors and percentage THD features are used for NILM. A.S. Bouhouras et al. [31] employed a simple lookup table and used the summation of the first three odd harmonic phasors. A non-intrusive discriminant analysis of loads based on PQ data was reported in [32], where classifiers based on linear and quadratic discriminant analysis were implemented. Household appliance classification using lower odd-numbered harmonics and the bagging decision tree approach was detailed in [33]. A.S. Bouhouras et.al [34] employed entropies and spectral band energy to specified frequency bands of the current spectrum to simplify the identification of appliances and accomplished good results. All of these methods adopted deep learning, machine learning and/or statistical methods. Moreover, these approaches considered DR management from an energy conservation perspective but not from a PQ perspective.

Consumers are not paying for the harmonic power induced by nonlinear appliances, which are up to 20% above their real consumption, as energy meters ignore harmonic currents. Harmonics, due to the low electronic power loads of consumers, are disregarded due to their low power consumption; however, the harmonic diction levels are very high. This issue was highlighted by a survey report in 2015 by the Government of India in the name of Swachh Power [35]. There are various ISO(International Organization for Standardization) standards and guidelines such as IEC (International Electrotechnial Commission) 61000-3-2, 61000-4-30 and IEEE (The Institute of Electrical and Electronics Engineers) 519-2014 for harmonic estimation and control [35].

The THD percentages of loads were established by O Deepu et.al [36] for three different loads—CFL, personal computer, and uninterrupted power supply—and were found to be distinct. The percentage THD of current harmonics for these loads is found to be 72, 125, and 35, respectively. Marko Dimitrijević [17] measured the first 39 harmonics for six different appliances and various combinations of these appliances in operation.

In the opinion of authors of this article, the quality of power is more critical for utilities than for power savings in smart homes. The authors would like to approach DR from a PQ point of view rather than to reduce power consumption. If any conventional methods or intrusive methods are used to identify the load patterns, they would not throw light on the harmful impact of harmonics introduced by the pervasive use of low-power nonlinear loads, and hence would not lead to improving PQ from a harmonics perspective. Two standards, namely, IEEE 519-2014 and IEC 61000-3-2 and the Central Electricity Authority guidelines recommend reducing the percentage THD from both utility and consumer perspectives. The understanding of the authors of this article is that this approach is very much needed to impress upon consumers and utilities the urgency of this issue. The industry can adopt this solution if percentage THD is measured, and we offer insights into further actions that can be taken.

Low-power non-linear load harmonic compensation is not addressed individually; therefore, the authors understand that accurate estimation of low-power harmonics and their corresponding percentage THD will identify the consumer loads effectively. The authors propose to use the percentage THD of steady-state harmonics, which is distinct for individual appliances and different combinations of appliances. In this article, the authors propose a novel solution that uses the uniqueness of percentage THD to identify which set of appliances is in operation at any point in time without any ambiguity. This solution is the first of its kind, to the best of our knowledge, that establishes the efficient disaggregation of energy consumption at the appliance level. DR management using percentage THD is depicted in Figure 2.

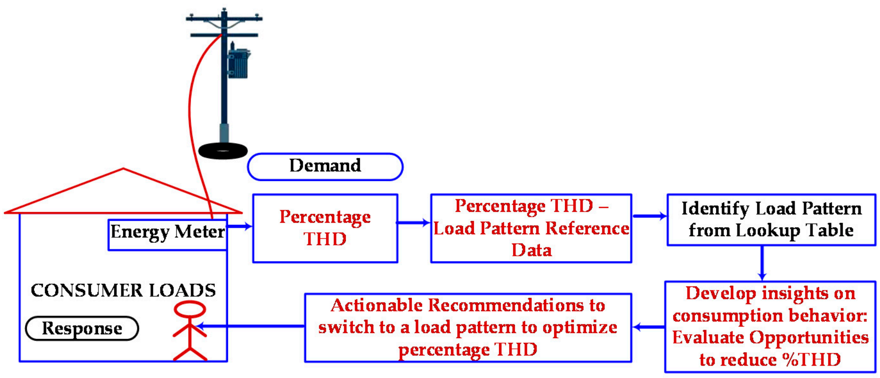

Figure 2. DR management in view of load monitoring using % Total Harmonic Distortion (THD).

NILM has been applied mostly to high-power appliances (50 W and above) from a power conservation perspective. There is insufficient research on percentage THD conservation induced by low-power nonlinear loads (less than 100 W), which is a big challenge of today in our distribution systems. For the first time, we tackle a problem that is not addressed as required by IEEE 519-2014, IEC 61000-3-2 standards and Central Electricity Authority guidelines. NILM is discussed in this article to bring the state-of-the-art research into context and to contrast with the proposed approach.

The major contributions are:

- The measurement of percentage THD using enhanced dual-spectrum line interpolated FFT (EDLIFFT) with a four-term minimal side-lobe window (4MSW) [37] for various real-world loads.
- The development of real-time load pattern identification for DR using a LabVIEW-based virtual instrumentation test bed.
- The recommendation of load patterns for DR management using a lookup table.

This paper is organized as follows: Section 2 discusses the method for the measurement of percentage THD. Section 3 describes the real-time measurement of percentage THD using EDLIFFT with a 4MSW on NI-LabVIEW for various combinations of real-world appliances. Section 4 discusses the results and establishes that percentage THD is a reliable single feature to identify the load consumption pattern; Section 5 concludes with a brief recap.

2. Measurement of Percentage THD, a Single Feature for Load Consumption Pattern Identification

PQ data are useful not only for assessing the quality of power for consumption and compensation aspects, but also for load pattern identification [32]. In particular, harmonic data can be found among PQ data. Among harmonic data, such as harmonic amplitudes, harmonic phases and percentage THD, the latter is found to be helpful to uniquely identify load patterns. Therefore, accurate measurement of percentage THD is essential for load identification. In general, the percentage THD of a current's harmonic signal is measured using FFT. If the measurements of harmonic orders are not accurate then the percentage THD value will be erroneous. FFT measurements have limitations such as spectral leakage and the picket fence effect [37,38]. Recently, EDLIFFT with a 4MSW for real-time harmonic estimation was proposed in [37], which overcame both the drawbacks of FFT. By using this algorithm, the harmonic orders are measured and the percentage THD of any given load pattern is computed as in Equation (1) [39,40]:

$$\textit{Percentage Current THD} = \frac{\sqrt{\sum_{n=2}^{H} I_n}}{I_{fund}} \quad (1)$$

where

H = harmonic order
I_n = n^{th} harmonic current
I_{fund} = fundamental current

Thus, we can employ percentage THD as a simple database lookup to find which combinations of appliances are in operation at any point in time. The rated power of all appliances is a known value, so we can compute the energy consumed by individual appliances for the time they spend operation. This lookup table is used to create the disaggregated load by appropriating the rated power of the appliance. The total sum of the active power at any point is compared to the power measured at the energy meter. This information, when applied with contextual data like occupancy, ambient temperature, etc., can deduce unnecessary use of appliances and can be shared with the customer suggest potential savings.

3. Real-Time Experimentation for Non-Intrusive Identification of Load Pattern (NIILP) Using Percentage THD Measurement

In this section, real-time experimentation for NIILP using percentage THD measurement is described. A National Instruments (NI) compact reconfigurable input–output system (cRIO) 9082-based virtual instrumentation experimental setup is developed for validating the proposed NIILP. It is one of the potential real-time hardware tools for percentage THD measurement, as per the requirements of international standards such as IEEE 519,1159 and IEC 61000-4-60. The NI-cRIO 9082 has a Field-Programmable Gate Array (FPGA) architecture which is equipped with an Intel Core-i7 dual-core Central Processing Unit (CPU) with a frequency of 1.33 GHz, 2 GB of DRAM (Dynamic random access memory), 32 GB of ROM (read only memory), and a Xilinx Spartan-6 LX150 FPGA. It consists of a reconfigurable embedded chassis with an integrated intelligent real-time controller and data acquisition modules for analog signal acquisition [41,42]. EDLIFFT with 4 MSW was deployed in the LabVIEW-configured host computer and interfaced to the NI LabVIEW-powered NI-cRIO 9082 through the TCP/IP interface, as illustrated in Figure 3. Most of the typical real-world loads are CFL, LED, fan and PC. Hence, the CFL, LED, exhaust fan and SMPS of the personal computer, which is connected to the single-phase 230 V, 50 Hz utility supply mains, are considered for computing the percentage THD using EDLIFFT with a 4MSW. The load current waveforms are acquired from supply mains and processed to the NI-cRIO 9082 using the NI-9227 current input module.

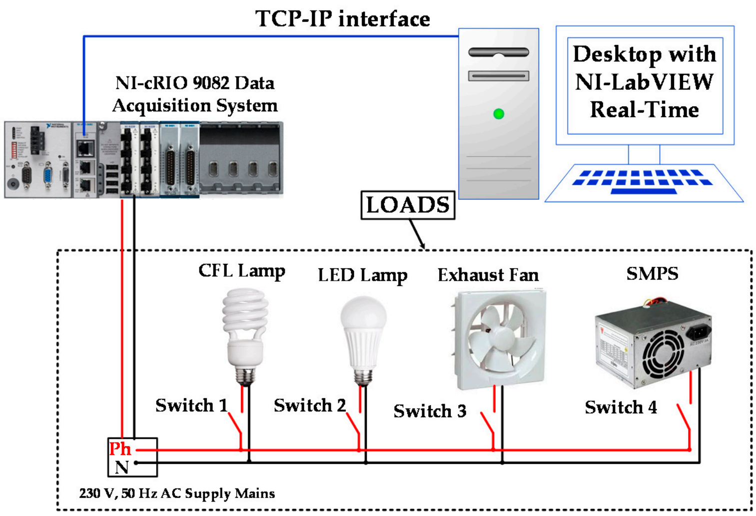

Figure 3. Hardware schematic for percentage THD computation.

A detailed flow-chart of the percentage THD measurement method is described in Figure 4. The percentage THD is measured by using the data obtained from EDLIFFT with 4 MSW. The individual switches turn the loads ON and OFF to verify the different load combinations. Thereby, the percentage THD of each combination is computed by the algorithm given in Figure 4.

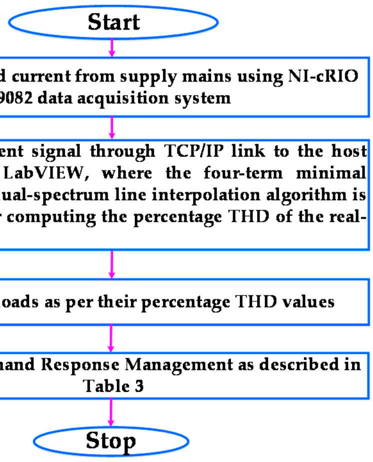

Figure 4. Flow chart for percentage THD computation.

4. Results and Discussion

The real-world load current waveforms acquired by the NI-cRIO 9082 for various load combinations are depicted in Figures 5–7. Initially, single-load operation is acquired and the individual load current waveforms of the CFL, LED, exhaust fan and SMPS of the PC are illustrated in Figure 5. From the individual load waveforms depicted in Figure 5a–d, it can be observed that no two waveforms are found to be the same shape due to the harmonic pollution. Moreover, these waveforms are highly nonlinear. Therefore, the percentage THD values of these loads are found to be unique in nature.

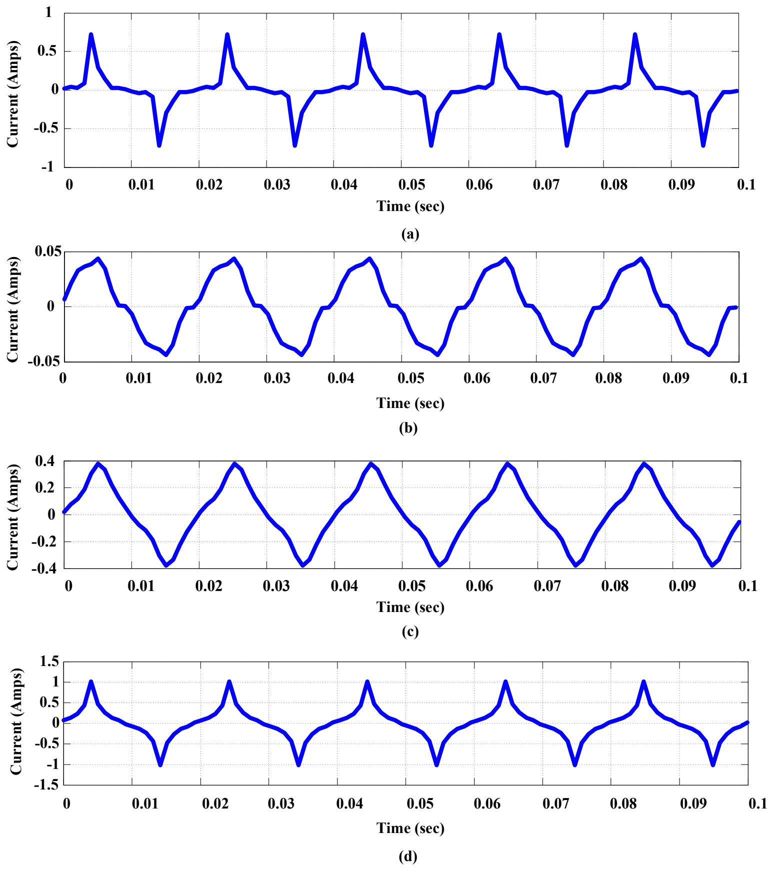

Figure 5. Individual single loads. (**a**) CFL load waveform; (**b**) LED load waveform; (**c**) exhaust fan waveform; (**d**) SMPS of the PC waveform.

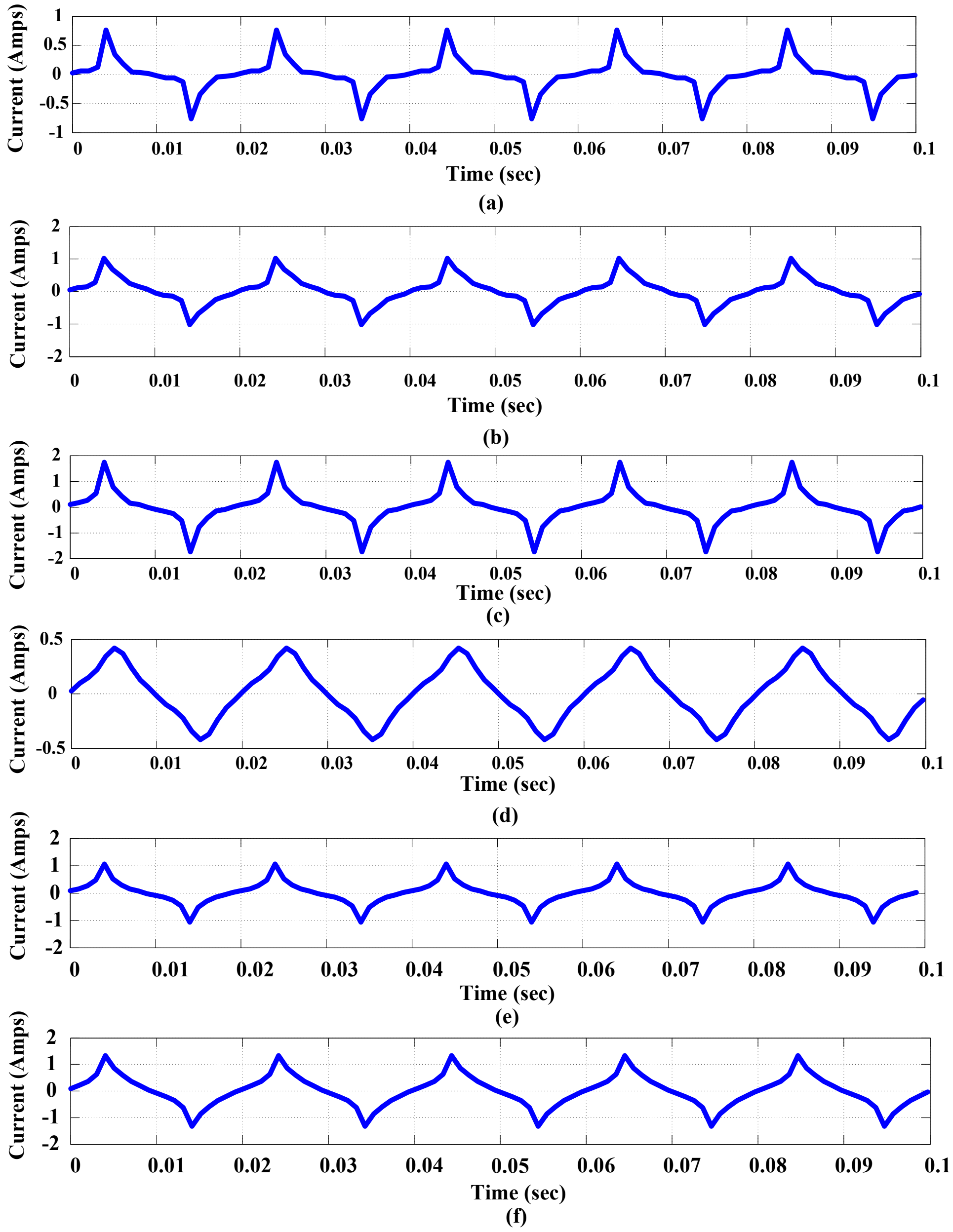

Figure 6. Any two loads. (**a**) CFL + LED load waveform; (**b**) CFL + exhaust fan load waveform; (**c**) CFL + SMPS of the PC load waveform; (**d**) LED + exhaust fan load waveform; (**e**) LED + SMPS of the PC load waveform; (**f**) exhaust fan + SMPS of the PC load waveform.

Any two real-world load combinations are monitored by turning ON their corresponding load switches. The waveforms acquired from the NI-cRIO 9082 for any two real-world load combinations are shown in Figure 6. From the figures, it is observed that no two waveforms are found to be the same shape due to the harmonic distortion. Therefore, the percentage THD values of these load patterns are found to be unique in nature.

Any three load combinations are monitored by turning ON their corresponding load switches and the three load combination waveforms of the CFL, LED, exhaust fan and SMPS of the PC are depicted in Figure 7. It is observed from Figure 7 that no two waveforms are found to be the same due to the harmonic pollution.

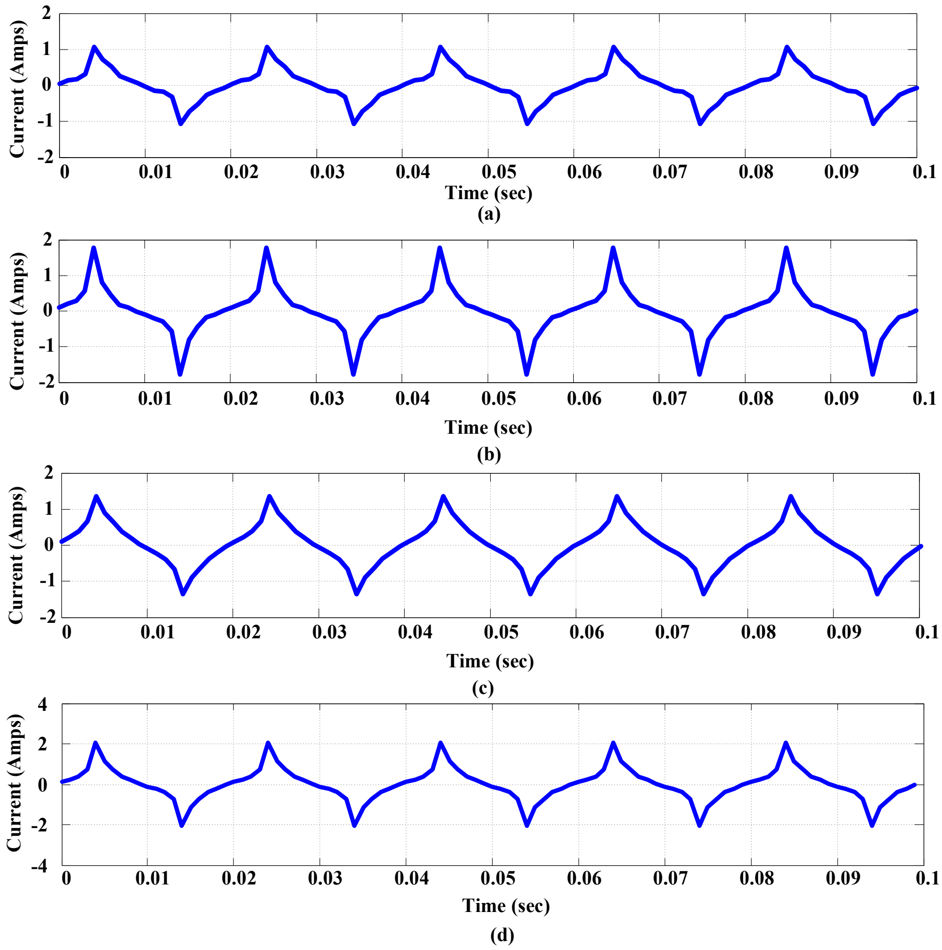

Figure 7. Any three loads. (**a**) CFL + LED + exhaust fan load waveform; (**b**) CFL + LED + SMPS of the PC load waveform; (**c**) LED + exhaust fan + SMPS of the PC load waveform; (**d**) CFL + exhaust fan + SMPS of the PC load waveform.

The load waveform at the supply mains when all the loads are active is illustrated in Figure 8. This waveform is also found to be quite different from the other load pattern waveforms.

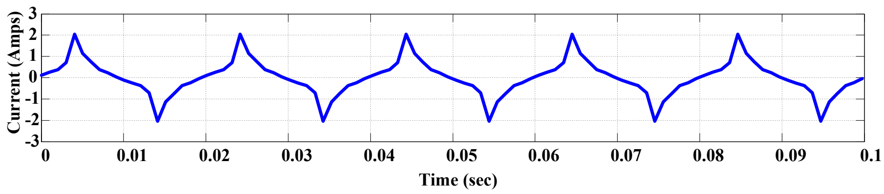

Figure 8. All four loads. CFL + LED + exhaust fan + SMPS of the PC load waveform.

From single-load operation to four-load operation, the load current waveforms are unique, indicating that the percentage THD is different for all load combinations. Therefore, percentage THD can be safely used for load identification effectively. The percentage THDs measured by EDLIFFT with a 4MSW using an NI-cRIO 9082 data acquisition system described in Figure 4 are tabulated in Table 2.

Table 2. Percentage THD for all 15 load patterns in real time.

S.No	Combinations of Different Appliances	CODE	Power (Watts)	%THD
1	CFL	1 0 0 0	85	123.395
2	LED	0 1 0 0	9	19.7279
3	Exhaust Fan	0 0 1 0	20	21.3272
4	SMPS of PC	0 0 0 1	200	92.763
5	CFL + LED	1 1 0 0	94	112.457
6	CFL + Exhaust Fan	1 0 1 0	105	72.007
7	CFL+ SMPS of the PC	1 0 0 1	285	105.402
8	LED + Exhaust Fan	0 1 1 0	29	20.3095
9	LED + SMPS of the PC	0 1 0 1	209	86.1947
10	Exhaust FAN + SMPS of the PC	0 0 1 1	220	59.6673
11	CFL+ LED + Exhaust Fan	1 1 1 0	114	68.3618
12	CFL+ LED + SMPS of PC	1 1 0 1	294	101.076
13	LED + Exhaust Fan + SMPS of PC	0 1 1 1	229	57.0561
14	CFL+ Exhaust Fan + SMPS of PC	1 0 1 1	305	80.1096
15	CFL+ LED + Exhaust Fan + SMPS of PC	1 1 1 1	314	77.6529
		Standard Deviation		**33.069**

Our experiment was conducted and established that percentage THD uniquely identifies all combinations of loads. The standard deviations of the percentage THD values indicate that they are all uniquely different. Hence, they are used in the primary key of a lookup table to discern the loads in operation based on the percentage THD. A load power versus percentage THD plot is depicted in Figure 9, where the percentage THDs are relatively different for the different load powers. The actionable recommendations are based on the possible shifting of load demand from the red region to the yellow region and from the yellow region to the green region for a better response in order to reduce harmonic pollution to the extent possible in the load consumption scenarios.

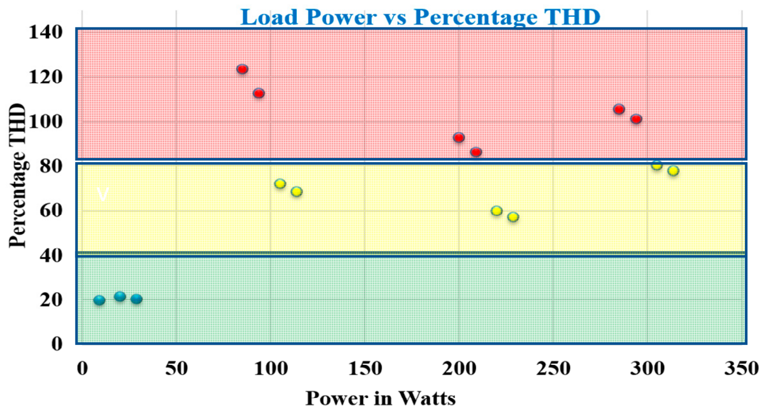

Figure 9. Load power versus percentage THD of the demand.

The recommendation chart for DR management in Table 3 establishes the opportunity to reduce percentage THD within premises. The consumer benefits from the increased life of his appliances and utilities benefit from the increased life of their equipment in the distribution system.

Table 3. Actionable insights for DR management.

Actionable Insights and Benefits										
Demand					Response				Benefits	
S.No	**CODE**	**Power**	**%THD**	**Actionable Insights**	**S.No**	**CODE**	**Power**	**%THD**	**Change in %THD**	**Change in Power**
1	1 0 0 0	85	123.395	Turn off CFL	2	0 **1** 0 0	9	19.7279	−84.0124	−89.4118
2	0 1 0 0	9	19.7279	NR [1]	NR	0 1 0 0	9	19.7279	0	0
3	0 0 1 0	20	21.3272	NR	NR	0 0 1 0	20	21.3272	0	0
4	0 0 0 1	200	92.763	Turn off LED for daytime	**9**	0 **0** 0 1	209	86.1947	−7.08073	4.5
5	1 1 0 0	94	112.457	Turn off CFL	**2**	0 **1** 0 0	9	19.7279	−82.4574	−90.4255
6	1 0 1 0	105	72.007	Turn off CFL	**8**	0 1 1 0	29	20.3095	−71.7951	−72.381
7	1 0 0 1	285	105.402	Turn off CFL for daytime	**4**	0 **0** 0 1	200	92.763	−11.9912	−29.8246
8	0 1 1 0	29	20.3095	Turn off LED for daytime	**3**	0 0 1 0	20	21.3272	5.010955	−31.0345
9	0 1 0 1	209	86.1947	Turn off LED for daytime	-	0 1 0 1	209	86.1947	0	0
10	0 0 1 1	220	59.6673	NR	-	0 0 1 1	220	59.6673	0	0
11	1 1 1 0	114	68.3618	Turn off CFL	**8**	0 **1** 1 0	29	20.3095	−70.2912	−74.5614
12	1 1 0 1	294	101.076	Turn off CFL	**9**	0 **1** 0 1	209	86.1947	−14.7229	−28.9116
13	0 1 1 1	229	57.0561	Turn off LED for daytime	**10**	0 **0 1 0**	220	59.6673	4.576548	−3.93013
14	1 1 0 1	305	80.1096	Turn off CFL	**13**	0 1 1 1	229	57.0561	−28.7774	−24.918
15	1 1 1 1	314	77.6529	Turn off CFL	**13**	0 1 1 1	229	57.0561	−26.5242	−27.0701

[1] NR = no recommendation.

The change in power consumption and the change in percentage THD columns show these direct benefits by responding positively to the proposed recommendations, as appropriate.

C. Nalmpantis et al. [15] proposed qualitative and quantitative metrics for NILM, and the authors of this study applied the same metrics, which are presented in Table 4 below. The quantitative metrics clearly demonstrate the effectiveness of the proposed experimental approach over non-deterministic NILM methods.

Table 4. Quantitative metrics for NILI–percentage THD.

Quantitative Metric Category	Quantitative Metrics	%THD	Other NILM Methods
Feature selected	THD Sampling rate	Medium	High
Accuracy	Disaggregation percentage(D)	100	<100
	Disaggregation Error (DE)	0	>0
	Precision(P)–TP [1]/(TP + FP [2])	1	<1
	Recall (R)-P/TP+FN	1	<1
	Accuracy (Acc) = (TP + TN [3])/(TP+TN+FP+FN [4])	1	<1
	F-measure (f1) 2 *P *R/(P + R)	1	<1
No training	User interaction	Low	
Real-time capabilities	Depends on algorithm's computational complexity (computational cost)	Low	Low
Scalability	Algorithm computational complexity (simple algorithm scales better)	High	High
Identification factor	Standard deviation (FATσ) of %THD	33.069	NA
Generalization	Generalization over unseen houses	High	Medium

[1] TP = true positive; [2] FP = false positive; [3] TN = true; [4] FN = false negative.

5. Conclusions

This paper presents a deterministic approach, using percentage THD to identify load consumption patterns through EDLIFFT with a 4MSW in the NI-LabVIEW program, for various combinations of loads in real time, and demonstrates that the percentage THD value effectively identifies various load combinations. The proposed method for the non-intrusive identification of the load pattern is essential for responsible electricity consumption, as it contributes to raising awareness about the quality of electricity, encourages countries/companies to use harmonic-free devices and calls for policy changes to promote harmonic-free appliances (compensation at the source) so the grid can become free of harmonics. Harmonics contribute 20% more than the real consumption billed to the consumer, which can be reduced to help with the cost of energy for utilities, leading to better margins, which are otherwise considered as losses. Utilities and consumers also benefit from the increased lifetime of their equipment and appliances, respectively. Our DR chart highlights the change in power and the change in percentage THD, then the customer acts on the DR management system's recommendations. Standard deviation, a measure of the dispersion of values, indicates the differentiation of load patterns without ambiguity. Since both percentage THD against all possible combinations of loads are measured and put into a lookup table and recommendations are also chosen in advance, the performance of DR is fairly good for real-time DR management from a PQ perspective.

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